FUZZY TRAVERSABILITY INDEX: A NEW CONCEPT FOR TERRAIN-BASED NAVIGATION

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Abstract

Fuzzy Traversability Index is introduced in this paper as a new and simple measure for quantifying the ease of traversal of natural terrains by field mobile robots. This index provides a simple means for incorporating the terrain quality data into the robot navigation strategy, and is used for terrain-based navigation of field mobile robots. The Traversability Index is expressed by fuzzy sets that quantify the suitability of the terrain for traversal based on its geometrical and physical properties, such as slope, roughness, and hardness. This descriptive representation of terrain traversability in a natural language using linguistic variables and conditional statements is easily comprehensible, more appealing, and closer to human intuition than a mathematical formulation of traversability. A set of fuzzy navigation rules is developed using the Fuzzy Traversability Index to guide the robot toward the safest and the most traversable terrain. In addition, another set of fuzzy rules is developed to drive the robot from its initial position to a user-specified goal position. These two rule sets are integrated in a two-stage procedure for autonomous robot navigation without a priori map-based knowledge about the environment. In the first stage, the traverse-terrain and seek-goal rule sets make their individual, independent recommendations for robot turn and move commands. In the second stage, these recommendations are integrated by using appropriate weighting factors to generate the combined, coordinated recommendation for the robot navigation based on the robot status. Three simulation studies are presented to demonstrate the capability of the mobile robot to reach the goal safely while avoiding impassable terrains.

1 Introduction

Although considerable research has been conducted on mobile robot navigation in recent years, the bulk of this research is focused on *indoor* robots operating in highly-structured, known, and *human-made* environments. Typically, the environment consists of a flat, smooth, horizontal floor on which the robot moves. The navigation system for an indoor mobile robot typically consists of two components: goal-based navigation for target seeking and obstacle-based navigation for collision avoidance. While these two components are adequate for indoor mobile robots, these capabilities are insufficient for *outdoor* (field) mobile robots that operate on unstructured, unknown, and *natural* terrains. For field mobile robots, the terrain plays an important role in the navigation logic. In fact, the terrain characteristics are the key features that distinguish field robot navigation from indoor robot navigation. Unlike their indoor counterparts, field robots must deal with rugged and rough natural terrains, and make real-time judgments and decisions based on the terrain quality. The navigation system for a field mobile robot must therefore account for the terrain information obtained from on-board sensors, in addition to the goal seeking and collision avoidance components. The inclusion of the terrain quality data into the navigation logic adds a third dimension of *terrain-based navigation* that complements the existing two dimensions of goal-based navigation and obstacle-based navigation.

The classical methods for field robot navigation focus on a binary representation of the terrain from an obstacle occupancy point of view. Specifically, the terrain around the robot is divided up into a grid and binary values (0 or 1) are assigned to the cells in the grid, where 0 represents a traversable obstacle-free cell and 1 denotes an untraversable cell occupied by an obstacle. Recent experience in driving the Sojourner rover on Mars revealed that a binary representation can result in halted motions, often leaving the rover in an undesirable situation [1]. A more comprehensive approach to field robot navigation is to characterize the presence of an obstacle in a grid cell using a non-binary representation. In this setting, a grid cell is not assigned a binary value, but instead is given a continuous value that represents the probability distribution for occupancy of the grid cell by an obstacle [2]. Even these comprehensive representations only account for the *obstacle* presence and disregard the terrain properties. As such, they facilitate obstacle-based navigation but do not address terrain-based navigation. There are in fact only a few existing methods available for evaluating terrain characteristics as it relates to field robot navigation. In the current methods [3-9], traversability is defined as a non-binary mathematical function of the slope and roughness of the terrain. Slope is usually determined by finding the least-squares fit of a plane covering the area centered at a pixel in the video images obtained from on-board cameras. Given this slope evaluation, roughness is calculated as the residual of the best plane fit – in effect, it represents the maximum height of the rocks extending above (or below) the fitted plane. Traversability is thus defined on a pixel-by-pixel (or grid-based) basis, in which the slope and roughness of the terrain are determined as a mathematical function of slope and roughness of each individual grid cell. A traversable path for the rover to follow is then constructed based on the calculated traversability of each cell. This traversability analysis uses, in effect, a go/no-go pseudo-obstacle assessment scheme, rather than a true terrain evaluation approach. In fact, if all extracted candidate cells contain one slender, tall rock (such as an obelisk) within an otherwise smooth area, a traversable path cannot be constructed using the existing methods. Furthermore, analytical representations of terrain traversability, such as those defined in [3-9], rely on accurate interpretations of the video images obtained from on-board cameras, as well as the mathematical definition of the traversability function. The video images are usually contaminated by noise, calibration errors, and other sources of imprecision and ambiguity. The mathematical definition of the traversability function is also subjective and somewhat arbitrary, leading to different conclusions based on the choice of the traversability function. Alternative methods for analytical representation of the terrain are described in [10-11], but suffer from the same deficiencies.

In this paper, a new concept called *Fuzzy Traversability Index* is introduced for the first time for field mobile robots operating on natural terrains. This index is expressed by *linguistic* variables represented by fuzzy sets that quantify the suitability of the terrain for traversal based on its geometrical and physical properties, such as slope, roughness, and hardness. In contrast to the existing methods [3-11], the proposed Traversability Index provides a *fuzzy* characterization of the terrain properties that affect its traversability. This approach is intuitive and easily comprehensible because of the use of *linguistic* variables such as STEEP, ROCKY, and SOFT to describe the terrain. The rule set that defines the Fuzzy Traversability Index verbalizes the human judgment of the terrain in a natural language such as English, which is more appealing than the existing mathematical functions [3-11]. The fuzzy logic framework also inherently deals with the considerable uncertainty and ambiguity associated with extracting the terrain information from the scene images. Using the Fuzzy Traversability Index, a set of fuzzy navigation rules is developed to guide the robot toward the safest and the most traversable terrain. This rule set is integrated with fuzzy rules for goal seeking to obtain an autonomous navigation strategy for a field mobile robot that requires no *a priori* map-based knowledge about the environment. The fuzzy logic rules presented in this paper are intended to capture the reasoning and decision-making of an expert human driver navigating a mobile robot on a natural terrain.

The paper is structured as follows. In Section 2, the Fuzzy Traversability Index is defined using the fuzzy logic framework. A set of fuzzy navigation rules based on this index is presented in Section 3. Section 4 discusses fuzzy logic rules for the robot goal seeking component. The integration of the terrain traversing and goal seeking fuzzy rule sets is described in Section 5. Illustrative computer graphical simulations are presented in Section 6 for proof-of-concept and demonstration. The paper is concluded in Section 7 with a brief review and future plans.

2 Fuzzy Traversability Index for Field Mobile Robots

This section develops, for the first time, the *Fuzzy Traversability Index* as a new and simple measure for quantifying the ease of traversal of natural terrains by field mobile robots. This index provides a succinct form for representation of the terrain quality in the robot navigation logic, and for encapsulating the terrain quality data into a single index. Fuzzy logic is the natural framework for definition of the Traversability Index because of the imprecision of the on-board sensors that measure the terrain quality, as well as the approximation inherent in terrain classification. The multi-valued "grade" of terrain traversability offered by the Fuzzy Traversability Index is appealing as a more comprehensive alternative to the abrupt binary (0 or 1) representation used for representing the absence or presence of an obstacle. Several options are available for defining the Fuzzy Traversability Index as a function of the terrain geometrical and physical properties. In this paper, the Traversability Index τ is defined by fuzzy relations in terms of three characteristics of the terrain: the slope α, the roughness β, and the hardness γ, where α, β, and γ are expressed by fuzzy sets as described below.

2.1 Terrain Slope α

The terrain slope α can be extracted from the scene images obtained by a stereo vision system mounted on the robot [3-9]. Typically, α is computed as the gradient of the geometric plane that best fits the terrain of interest in the least-squares sense. The slope α is represented by the three fuzzy sets { FLAT, SLOPED, STEEP }. The membership functions of these sets are user-defined trapezoids as shown in Figure 1a, where the abscissa α is the magnitude of the terrain slope and the ordinate $\mu(\alpha)$ is the degree-of-membership. Note that the slope can be either a positive quantity representing a dune or a hill, or a negative quantity representing a crater or a downward surface. Observe that precise measurement of the terrain slope is *not* needed when using the fuzzy logic framework.

2.2 Terrain Roughness β

As pointed out earlier, the existing methods for roughness evaluation [3-9] compute terrain roughness as the residue to the least-squares plane fit. These methods are sensitive to measurement errors and tend to produce counter-intuitive results when applied to a region containing one large rock located within an otherwise smooth terrain. In this paper, we develop a different approach by defining terrain roughness β as a function of rock size δ and rock concentration ω on the given terrain, where size is determined by the average height of the rocks and concentration is defined by the relative size of the region occupied by the rocks. Thus, a region with a large number of large rocks will have high roughness, a region containing a small number of small rocks will have low roughness, and a region containing a small number of large rocks will have a medium roughness measure. This approach to roughness evaluation mimics the intuitive judgment of a human observer. Since we understand size and concentration in linguistic terms, we shall represent the size and concentration values by linguistic variables represented by fuzzy sets. The rock size δ can be represented by the two fuzzy sets { SMALL, LARGE }, with the user-defined trapezoidal membership functions shown in Figure 1b. Similarly, the rock concentration ω is represented by the two fuzzy sets { FEW, MANY }, with the user-defined trapezoidal membership functions depicted in Figure 1c. The terrain roughness β can then be expressed in terms of δ and ω using a set of simple fuzzy relations. Let β be represented by the three fuzzy sets { SMOOTH, ROUGH, ROCKY }, where the user-specified trapezoidal membership functions are shown in Figure 1d. The dependence of β on δ and ω can then be expressed by a set of four simple fuzzy rules as:

- IF δ is SMALL AND ω is FEW, THEN β is SMOOTH.
- IF δ is SMALL AND ω is MANY, THEN β is ROUGH.
- IF δ is LARGE AND ω is FEW, THEN β is ROUGH.
- IF δ is LARGE AND ω is MANY, THEN β is ROCKY.

The above rule set is summarized in Table 1a. These fuzzy rules capture the intuitive definition of terrain roughness by a human observer. The rules allow the roughness definition to be robust with respect to measurement errors encountered in extracting the size and concentration information from the terrain scene images. Thus the precise measurements of the rock size δ and the rock concentration ω are *not* needed, because of the multi-valued nature of the fuzzy sets used to describe them.

2.3 Terrain Hardness γ

While the slope and roughness provide an adequate representation of the terrain from a *geometrical* perspective, they do not convey any information about the *physical* properties of the terrain as it relates to the mobile robot. This aspect of the terrain is particularly important from the load bearing and traction points of view, and is captured by the terrain hardness γ discussed briefly in this section.

From a navigation standpoint, a terrain can have very desirable geometrical properties (such as a smooth, flat surface), yet have a highly undesirable physical property (such as being too soft) that can cause trapped wheels and loss of traction for the robot. A smooth, flat surface composed of soft, fine-grain sand is clearly undesirable from the robot traversability point of view. Therefore, the degree to which the terrain can support the robot and its traction is also an important factor. It is conceivable for the mobile robot to possess sensing devices that measure the "hardness" of the local terrain and assess its suitability for traversal. For instance, one concept is a non-contact on-board sensor that consists of a pneumatic probe which will discharge a puff of air toward the ground surface and a laser displacement sensor that will detect the associated ground displacement. For "soft" ground, the detected surface displacement will be very large and for "hard" ground, the displacement value will be minimal. Another concept is a small force sensor carried by a simple on-board mechanism that makes physical contact with the nearby surfaces and senses the resulting contact forces [12] (analogous to a blind person with a walking stick). A third approach is texture-based measurement, where the surface hardness is inferred from the textural composition of the surface. Similar to the human recognition of soft sand versus compacted soil from its textural appearance, we can conceive a sensor unit composed of a video camera and a neural network-based processing stage, where the network is trained using several known samples. This unit can broadly categorize the surface hardness on the basis of its textural signatures. Regardless of the specific sensor technology used for surface hardness evaluation, this class of sensors will enable the robot to distinguish hazardous soft sandy regions from safe hard compacted soil.

Once the surface hardness γ is measured by an on-board sensor, it can be represented by the three fuzzy sets { SOFT, MEDIUM, HARD }, with the associated user-defined trapezoidal membership functions shown in Figure 1e. Note that precise measurement of the terrain hardness γ is *not* needed because of the multi-valued nature of the fuzzy sets.

2.4 Fuzzy Traversability Index τ

The Traversability Index τ is defined by a set of fuzzy relations in terms of the slope α, the roughness β, and the hardness γ of the terrain. In the framework of fuzzy logic, the *Cartesian product* is used to represent fuzzy functional relations [13]. Let $A = \{A_1, A_2, A_3\}$, $B = \{B_1, B_2, B_3\}$, and $C = \{C_1, C_2, C_3\}$ represent, respectively, the fuzzy sets defined on the input variables α, β, and γ. The Cartesian product of these input fuzzy sets is the output fuzzy set $T = A \times B \times C$ with the membership function defined by $\mu(\tau) = \mu(\alpha) * \mu(\beta) * \mu(\gamma)$, where $*$ denotes one form of the fuzzy set union ("and") operation and T is the fuzzy set of the output variable τ. The Traversability Index τ is represented by the three fuzzy sets $T =$ { LOW, MEDIUM, HIGH }, with the user-defined trapezoidal membership functions shown by solid lines in Figure 1f. In the context of the Traversability Index τ, the Cartesian product functional relation can be represented by a set of nine simple fuzzy rules as follows:

- IF α is STEEP OR β is ROCKY OR γ is SOFT, THEN τ is LOW.
- IF α is FLAT AND β is SMOOTH AND γ is HARD, THEN τ is HIGH.
- IF α is FLAT AND β is ROUGH AND γ is HARD, THEN τ is HIGH.
- IF α is SLOPED AND β is SMOOTH AND γ is HARD, THEN τ is HIGH.
- IF α is SLOPED AND β is ROUGH AND γ is HARD, THEN τ is MEDIUM.
- IF α is FLAT AND β is SMOOTH AND γ is MEDIUM, THEN τ is MEDIUM.

- IF α is SLOPED AND β is SMOOTH AND γ is MEDIUM, THEN τ is MEDIUM.
- IF α is FLAT AND β is ROUGH AND γ is MEDIUM, THEN τ is MEDIUM.
- IF α is SLOPED AND β is ROUGH AND γ is MEDIUM, THEN τ is LOW.

This rule set, in effect, verbalizes the human intuitive judgment of the terrain traversability in a natural language (i.e., English). This fuzzy representation of the traversability index is more appealing than the existing mathematical formulations of the traversability function [3-11] because of the use of linguistic variables and conditional statements that are close to human reasoning and comprehension. The 3-dimensional rule set, shown as a 3-layer cube in Table 1b, summarizes the above rules used for the definition of the Traversability Index τ in terms of the slope α, the roughness β, and the hardness γ of the terrain. From rule 1, it is seen that terrains with high slope, rocky surfaces, or soft support are considered to be highly impassable and must be avoided (see the front, side, and bottom layers in the rule cube of Table 1b). When these extreme cases are excluded, the Traversability Index τ falls in the range of possible values spanned by the three fuzzy sets LOW, MEDIUM, and HIGH, depending on the slope, roughness, and hardness of the terrain (see the eight relevant cells in Table 1b). It is observed that, depending on the circumstances, other surface properties (in addition to slope, roughness, and hardness) can influence the terrain traversability and must be taken into account when defining the Fuzzy Traversability Index.

It must be pointed out that terrain traversability also depends heavily upon the mechanical design of the mobile robot, which determines its hill-climbing and rock-climbing capabilities. As such, mechanical features such as ground clearance, traction mechanism (wheeled, tracked, legged, and so on), and other robot characteristics should also play an important role in determining the value of the Traversability Index. Although this index can be defined as a complicated function of both the terrain properties and the robot parameters, the complications of such a formulation are hard to justify. Therefore, to simplify the formulation, we define the Fuzzy Traversability Index only as a function of the terrain properties. However, the definitions of the trapezoidal membership functions (such as the four corner coordinates of the trapezoids that represent α, β, γ, and τ) are adjusted depending on the particular mobile robot under study. This allows the *same* rule set shown in Table 1b to be used for different mobile robots. As a result, a terrain that has a LOW Traversability Index for one robot can possess a MEDIUM Traversability Index for another robot with a different mechanical design. For instance, the dotted line membership functions in Figure 1f correspond to a more capable mobile robot than the robot with the solid line membership functions.

The three-stage process for on-board assessment of terrain traversability is shown in the block diagram of Figure 2a. In the first stage, the sensing module (e.g., stereo cameras) generates the raw sensed data (i.e., video images) from the terrain. In the second stage, the features of the terrain (such as slope, hardness, and rock size and concentration) are extracted from the raw data. Finally, in the third stage, these features are inputted into the fuzzy logic engine which evaluates the terrain traversability, as described below.

The fuzzy logic process for computation of the Traversability Index τ consists of the following stages shown in the block diagram of Figure 2b. The terrain roughness β is first obtained by fuzzy inference using the on-board measurements of the terrain rock size and concentration δ and ω. The numerical values of the terrain slope α, the terrain roughness β, and the terrain hardness γ are then passed through the "fuzzification" stage to find the degrees-of-membership in their corresponding fuzzy sets. This data is then used to evaluate the Traversability Index based on the fuzzy rules given in Table 1b. This stage, which is referred to as "inference" in fuzzy logic, produces the activation levels or strengths of the rules that are "fired" using the max-min fuzzy inference method [13]. This information is then passed to the "defuzzification" stage where the numerical value of the Traversability Index τ is computed using the centroid defuzzification method [13]. Note that the fuzzy logic framework used for computation of τ only requires reasonable estimates of the terrain quality data α, β, and γ obtainable from inexpensive sensors that are expected to be imprecise. This method does *not* need expensive precision sensors that also require extensive processing of sensory data for precise interpretations.

2.5 Natural Terrain Classification Based on τ

The Fuzzy Traversability Index provides a basis for classifying natural terrains according to their ease of traversal by the field mobile robot. Using the fuzzy linguistic description of the Traversability Index τ, different regions of the natural terrain within the on-board sensor horizon can be classified into three categories based on their value of τ. The three fuzzy sets for τ can be interpreted as follows:

- LOW $\tau \rightarrow$ IMPASSABLE TERRAIN.
- MEDIUM $\tau \rightarrow$ PASSABLE TERRAIN.
- HIGH $\tau \rightarrow$ HIGHLY-PASSABLE TERRAIN.

This terrain classification can also be used for other applications, such as automated selection of spacecraft landing site based on aerial video imagery.

3 Terrain-Based Navigation using Fuzzy Traversability Index

In this section, the Fuzzy Traversability Index defined in Section 2 is used to develop simple rules for determination of the robot heading and speed on a natural terrain. In other words, the Fuzzy Traversability Index is used to navigate the robot toward the safest and the most traversable terrain. This index provides a simple means for incorporating the terrain quality data into the robot navigation strategy. The fuzzy logic framework has been used extensively for goal-based and obstacle-based navigation of indoor mobile robots in the past [see, e.g., 14-25], but not for terrain-based navigation. The control variables of the mobile robot are the translational speed v and the heading angle change $\Delta\theta$ per control cycle. We shall now discuss the fuzzy rules for determination of the robot heading angle change and the robot speed based on the Fuzzy Traversability Index. These rules mimic the driving decisions of an expert driver navigating the robot on a natural terrain. Note that in an earlier version of this paper [26], the Fuzzy Traversability Index is defined as a function of terrain slope and roughness only, and a different set of navigation rules is developed.

3.1 Turn Rules

It is assumed that the mobile robot can only move in the forward direction (i.e., reverse motion is not allowed). The 180° field of view in front of the mobile robot is partitioned into three 60° sectors, namely: front, right, and left, as shown in Figure 3a. These sectors are at a distance r from the mobile robot, where r defines the radius of the sensing envelope. As shown in Figure 3a, the "front" refers to the direction the robot is heading at present, and "right" and "left" directions begin at ±30° relative to the current robot heading. The terrain traversability data is assumed to be available in the three forward directions. Therefore, at any instant, three Traversability Indices are computed for the three possible traversable regions described above, namely: τ_f, τ_r, and τ_l. The nine turn rules are as follows:

- IF τ_f is MEDIUM AND τ_l is HIGH, THEN $\Delta\theta$ is LEFT.
- IF τ_f is MEDIUM AND τ_l is MEDIUM AND τ_r is HIGH, THEN $\Delta\theta$ is RIGHT.
- IF τ_f is MEDIUM AND τ_l is LOW AND τ_r is HIGH, THEN $\Delta\theta$ is RIGHT.
- IF τ_f is LOW AND τ_l is HIGH, THEN $\Delta\theta$ is LEFT.
- IF τ_f is LOW AND τ_l is MEDIUM AND τ_r is HIGH, THEN $\Delta\theta$ is RIGHT.
- IF τ_f is LOW AND τ_l is LOW AND τ_r is HIGH, THEN $\Delta\theta$ is RIGHT.
- IF τ_f is LOW AND τ_l is MEDIUM AND τ_r is MEDIUM, THEN $\Delta\theta$ is LEFT.
- IF τ_f is LOW AND τ_l is MEDIUM AND τ_r is LOW, THEN $\Delta\theta$ is LEFT.
- IF τ_f is LOW AND τ_l is LOW AND τ_r is MEDIUM, THEN $\Delta\theta$ is RIGHT.

where LEFT and RIGHT represent the fuzzy sets of the heading angle change $\Delta\theta$, with the user-defined triangular membership functions shown in Figure 3b. Tables 2a and 2b summarize the above turn rule set when τ_f is LOW and MEDIUM. Note that LEFT is chosen as the "preferred" direction of rotation in the above rule set when left and right regions are equally traversable.

Observe that no turn actions are needed when: (1) τ_f is HIGH, or (2) τ_f is MEDIUM when τ_l and τ_r are also LOW or MEDIUM (see Table 2b), or (3) τ_f is LOW when τ_l and τ_r are also LOW (see Table 2a). In these cases, nothing is gained by the rotational maneuver of the robot and therefore the current heading is maintained.

3.2 Move Rules

Once the region to be traversed by the robot is selected based on the relative values of τ, the robot speed v can be determined based on the value of the Traversability Index τ^* in the *selected* region. This determination is formulated as a set of three simple fuzzy rules for speed of traverse as follows:

- IF τ^* is LOW, THEN v is SLOW.
- IF τ^* is MEDIUM, THEN v is MODERATE.
- IF τ^* is HIGH, THEN v is FAST.

where SLOW, MODERATE, and FAST represent the three fuzzy sets associated with the robot speed v, with the user-defined trapezoidal membership functions shown in Figure 3c.

4 Goal-Based Navigation for Target Seeking

In this section, we present fuzzy rules for navigation of the robot from its current position to the desired goal position. Two sets of rules are developed for the robot speed v and the robot heading angle change $\Delta\theta$. The basic idea behind the navigation rules is that the robot tries to: (1) approach the goal with a speed proportional to the distance between the current position and the goal position, defined as the "position error" d, (2) rotate toward the goal position by nullifying the "heading error" ϕ, which is the angle by which the robot needs to turn to face the goal directly.

We shall now present the fuzzy navigation rules for goal seeking in the following subsections.

4.1 Turn Rules

The robot heading angle change $\Delta\theta$ depends on the heading error ϕ, where the angles are defined to be positive in the clockwise direction. The heading error ϕ has the fuzzy sets { GOAL-LEFT, HEAD-ON, GOAL-RIGHT }, with the user-defined triangular membership functions depicted in Figure 4a. The fuzzy rules for the robot turn are as follows:

- IF ϕ is GOAL-LEFT, THEN $\Delta\theta$ is LEFT.
- IF ϕ is HEAD-ON, THEN $\Delta\theta$ is ON-COURSE.
- IF ϕ is GOAL-RIGHT, THEN $\Delta\theta$ is RIGHT.

Note that the second rule retains the current heading of the robot toward the goal. It is seen that the robot heading angle change $\Delta\theta$ is only a function of the heading error ϕ, and is independent of the robot speed v.

4.2 Move Rules

The robot speed v is generated by the goal distance d. The goal distance or position error d has the fuzzy sets { VERY NEAR, NEAR, FAR }, with the user-defined trapezoidal membership functions depicted in Figure 4b. The fuzzy rules for the robot speed are as follows:

- IF d is VERY NEAR, THEN v is SLOW.
- IF d is NEAR, THEN v is MODERATE.
- IF d is FAR, THEN v is FAST.

It is seen that the robot speed v is only a function of the goal distance d, and is independent of the heading error ϕ.

5 Integration of Traverse and Seek Behaviors

In the preceding two sections, fuzzy rule sets are given for the two *independent* behaviors of terrain traversing and goal seeking. The rule set for each behavior is concerned solely with achieving its particular objectives, disregarding the constraints imposed by the other behavior. In this section, we discuss the integration of these two behaviors to obtain an autonomous navigation strategy for the mobile robot. A two-stage procedure is proposed for autonomous robot navigation without *a priori* map-based knowledge about the environment. In the first stage, the traverse-terrain and seek-goal rule sets make their individual, independent recommendations for robot speed and heading angle commands. In the second stage, these recommendations are integrated by using appropriate weighting factors to generate the combined, coordinated recommendation for the robot navigation based on the robot status.

Consider the robot navigation procedure shown in the block diagram of Figure 5a. Each of the two behaviors, traverse-terrain and seek-goal, generates a set of independent recommendations for v and $\Delta\theta$ based on its own objectives. These sets of recommendations $\{v^t\}, \{\Delta\theta^t\}$ and $\{v^s\}, \{\Delta\theta^s\}$ are then "weighted" by the crisp weighting factors t_w and s_w assigned to the outputs of the traverse-terrain and seek-goal behaviors, respectively. In other words, the final recommendations $\bar{v}$ and $\overline{\Delta\theta}$ result from defuzzification of the weighted aggregated outputs of the traverse-terrain and seek-goal rule sets. The weighting factors t_w and s_w represent the strengths by which the traverse-terrain and seek-goal recommendations are taken into account. These factors are represented by the fuzzy sets { NOMINAL, HIGH }. The associated triangular membership functions are depicted in Figure 5b, and have the central values of 1 and 10, respectively. Within this context, the traverse and seek weighting factors are assumed to have the fuzzy NOMINAL value except in the following extreme cases:

- IF τ^* is LOW, THEN t_w is HIGH.
- IF d is VERY NEAR, THEN s_w is HIGH.

The first rule implies that when the selected terrain is not easily passable by the robot, the recommendation of the traverse-terrain rule set is assigned a HIGH weighting factor with the central value 10 relative to the seek-goal recommendation which has the NOMINAL weighting factor with the central value 1. The second rule suggests that when the goal position is almost reached, the seek-goal recommendation takes on the HIGH weighting factor relative to the NOMINAL weighting factor for the traverse-terrain recommendation. Excluding these two extreme cases, the traverse-terrain and seek-goal recommendations for v and $\Delta\theta$ are combined using equal weightings of unity to obtain the final recommendations for the robot speed and heading angle change $\bar{v}$ and $\overline{\Delta\theta}$ that are passed to the robot motion control system for execution.

6 Illustrative Examples

In this section, three graphical simulation results are presented to demonstrate fuzzy logic-based robot navigation using the traverse-terrain and seek-goal rule sets developed in this paper. The simulations are performed using the Robot Graphical Simulator (RGS) developed at JPL. This simulator is written in Java and is platform-independent, running on both PC and Unix machines. The RGS provides an essential tool for visualization of the robot reasoning and decision-making capabilities using the fuzzy logic navigation rule sets. It depicts a terrain composed of regions with different grades of traversability, together with the initial and goal robot positions. The rule sets for the two behaviors, namely, traverse-terrain and seek-goal, are integrated in the RGS. A simple Graphical User Interface (GUI) is provided to issue robot motion commands and display the robot movements graphically under the fuzzy navigation rules.

Three case studies are presented in this section. In each case, the robot is required to move from a user-defined initial position to a designated goal position while avoiding regions of poor traversability identified on the terrain. The robot is equipped with on-board "software sensors" that can detect terrain traversability in the three forward regions out to a specified distance. In all case studies, the terrain has HIGH Traversability Index ($\tau > \tau_4$), unless stated otherwise.

6.1 Case Study One

In this case, there is a region with LOW Traversability Index (a crater with $\tau < \tau_1$) between the initial and the goal positions of the robot as depicted in Figure 6a. The robot is required to move from the initial position denoted by a hollow rectangle to the goal position shown by a solid rectangle while avoiding the impassable region identified by the black circle. This circle encloses the impassable region which can have any irregular geometrical shape. A circular safety region is also defined which is displaced from the original region by a user-specified stand-off distance. The path traversed by the mobile robot under the fuzzy traverse-terrain and seek-goal rule sets is shown by the dotted line in Figure 6a. The dots along the path represent the locations of the robot center-point at uniformly spaced time intervals of 200 msec. Therefore, a cluster of dots denotes slow robot motion, while a spread of dots represents fast motion.

In this simulation, the initial and goal positions are aligned and therefore the robot heads straight toward the goal initially. As soon as the robot detects the crater region using its software sensors, it deviates from its original straight path to the left to avoid this region. The left turn is chosen as the "preferred" direction of rotation as stated in Section 3.1. Once the robot clears the impassable region, it heads straight to the goal position again. It is seen that the test is successfully completed with the robot reaching the goal safely while avoiding the impassable terrain.

6.2 Case Study Two

In this case, there are two impassable regions between the initial and the goal positions of the robot as depicted in Figure 6b. The first region has high slope with the Traversability Index of LOW ($\tau < \tau_1$), and the second region is an area of high rock concentration also with the Traversability Index of LOW ($\tau < \tau_1$). The robot is required to drive to the goal position while avoiding both impassable regions identified by black circles with user-defined safety regions. Figure 6b depicts the path traversed by the robot. In this case, the robot turns right initially, heading straight toward the goal position. The straight path is perturbed when the robot's software sensors detect the impassable regions. This causes the robot to traverse a curved path to the goal that clears the impassable regions. It is seen that the test is successfully completed with the robot reaching the goal safely while avoiding both impassable terrains.

6.3 Case Study Three

In this case, there are three impassable regions between the initial and the goal positions of the robot as depicted in Figure 6c. The robot is required to drive to the goal position while avoiding the three regions. These regions are a high slope area with LOW Traversability Index (black circle with $\tau < \tau_1$), a crater with LOW Traversability Index (black circle with $\tau < \tau_1$), and an area of high rock density with LOW Traversability Index (black circle with

$\tau < \tau_1$). Each impassable region is surrounded by a user-defined safety zone shown by a circle. The path traversed by the robot under the fuzzy traverse-terrain and seek-goal rule sets is shown by the dotted line in Figure 6c. In this simulation, the robot heads initially toward the goal on a straight path. This path is subsequently modified when the impassable regions are detected, and the resulting curved path is shown in Figure 6c. It is seen that the test is successfully completed with the robot reaching the goal safely while avoiding the three impassable terrains. Observe that the clustered dots along certain portions of the path represent slowing down of the robot motion in those path segments.

7 Conclusions

The new concept of Fuzzy Traversability Index is introduced in this paper for field mobile robots operating on natural terrains. The fuzzy logic framework is used to define the Traversability Index in terms of the geometrical and physical properties of the terrain, such as slope, roughness, and hardness. A set of fuzzy navigation rules based on this concept is developed to guide the robot toward the most traversable terrain. These rules are then integrated with another set of fuzzy rules for goal seeking to obtain an autonomous navigation strategy for the mobile robot. The proposed Fuzzy Traversability Index encapsulates the terrain quality data into a single index, and utilizes this index in the robot navigation logic. This process disallows the robot from entering impassable terrains which compromise the robot safety.

Fuzzy logic provides a natural framework for formulating and expressing the characteristics of the terrain from a traversability perspective, and for incorporating this information in terrain-based navigation of field mobile robots. The use of linguistic variables represented by fuzzy sets and conditional IF ( ), THEN ( ) rule statements is simple, intuitive, and akin to the human reasoning and decision-making processes. A novel feature of the proposed approach is the utilization of the *regional* traversability information obtained from the terrain data for robot navigation. This information augments the *local* information obtained from en-route obstacles to provide a comprehensive approach for autonomous robot navigation that requires no *a priori* map-based knowledge about the environment. Future research is focused on implementation and verification of the proposed approach on a commercial mobile robot designed for field operations [27-28].

8 Acknowledgments

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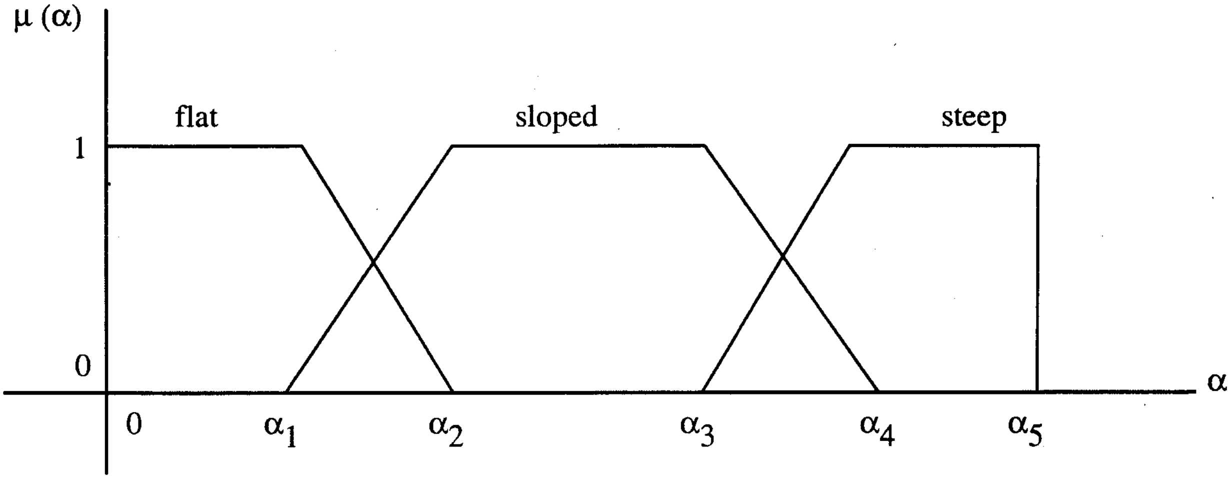

Figure 1a. Membership functions for terrain slope α

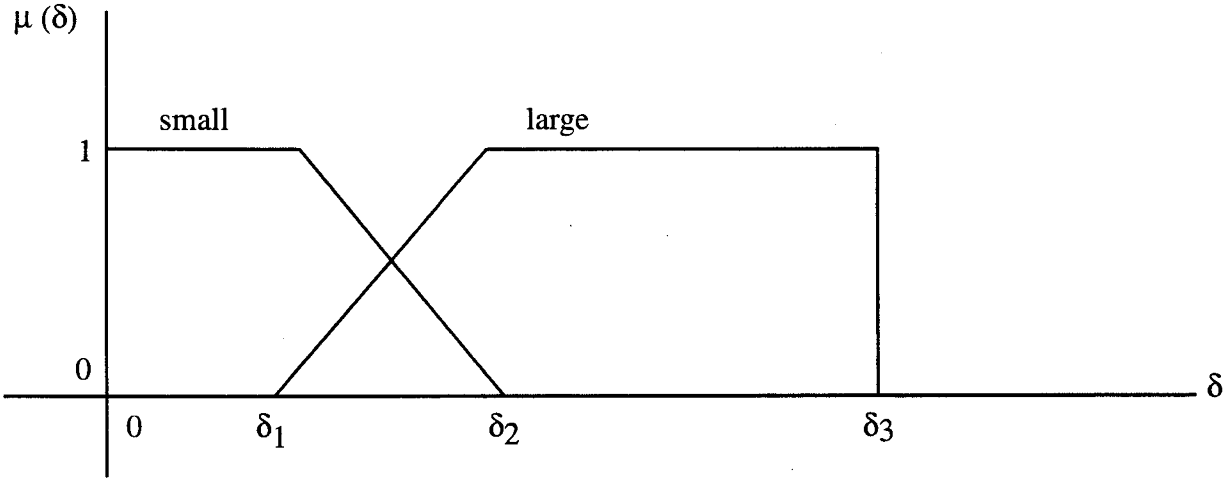

Figure 1b. Membership functions for rock size δ

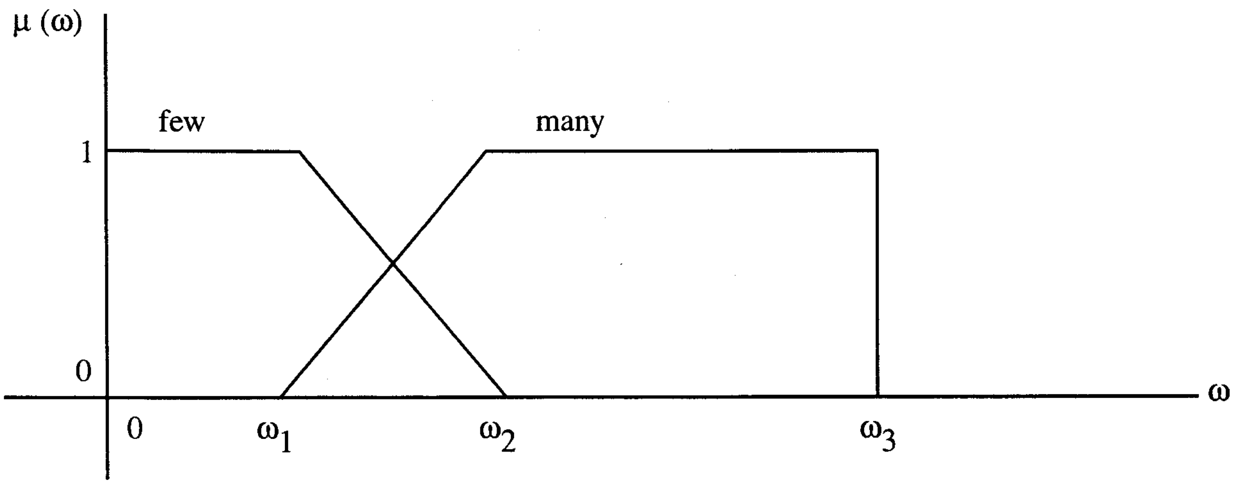

Figure 1c. Membership functions for rock concentration ω

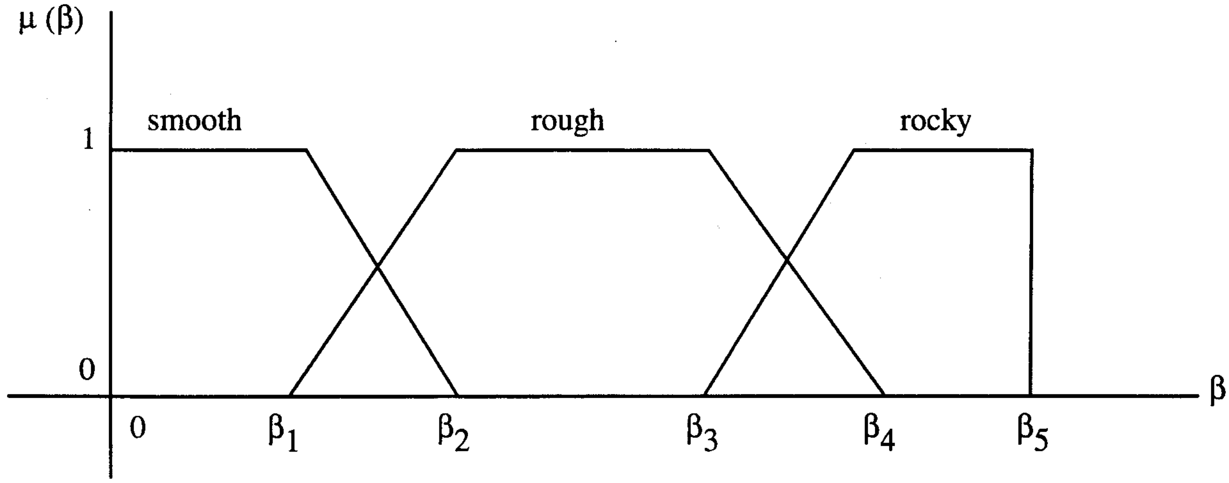

Figure 1d. Membership functions for terrain roughness β

rock size δ \ rock concentration ω	few	many
small	smooth	rough
large	rough	rocky

Table 1a. Rule set for terrain roughness β

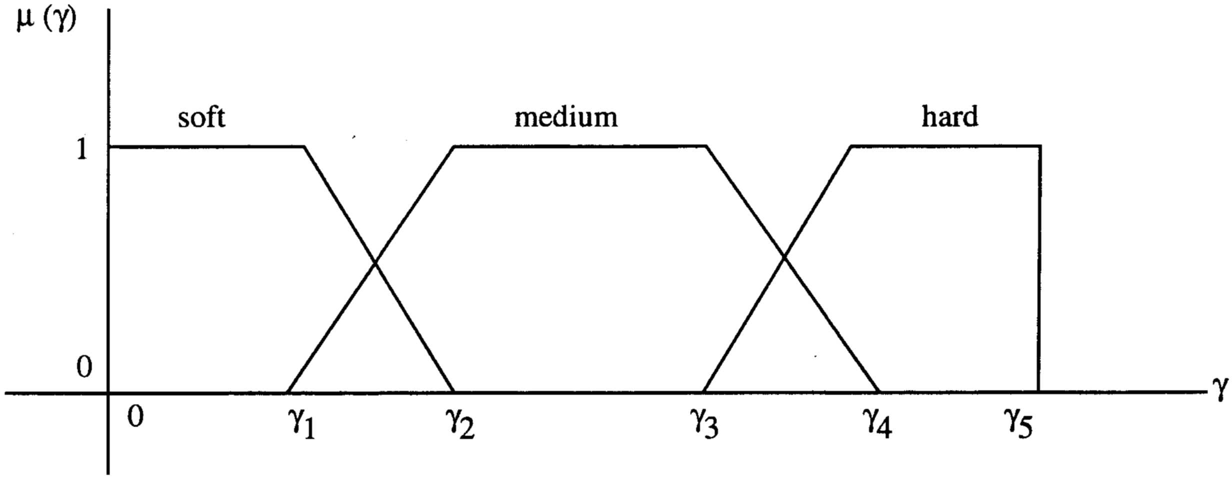

Figure 1e. Membership functions for surface hardness γ

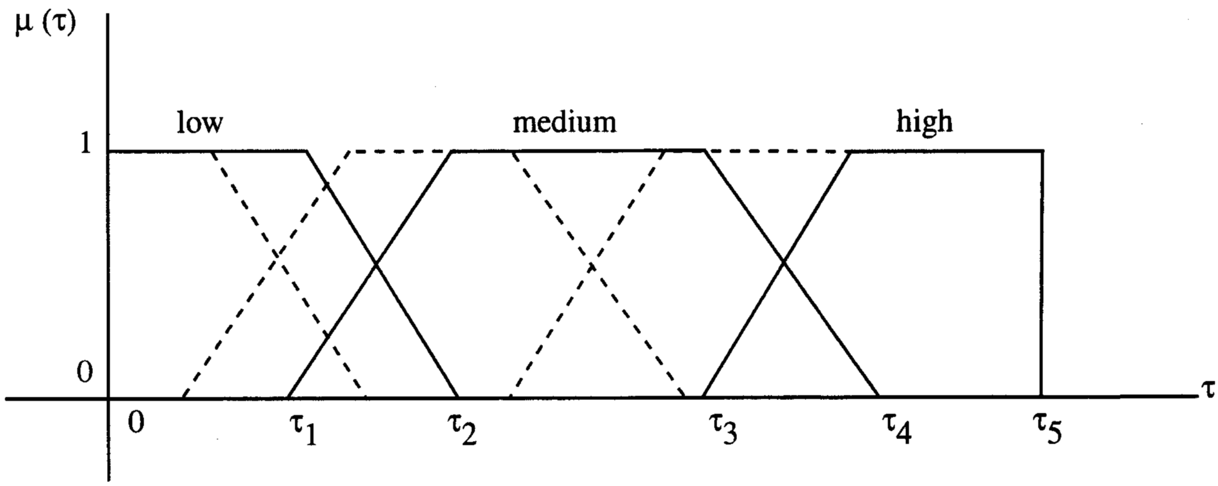

Figure 1f. Membership functions for Traversability Index τ

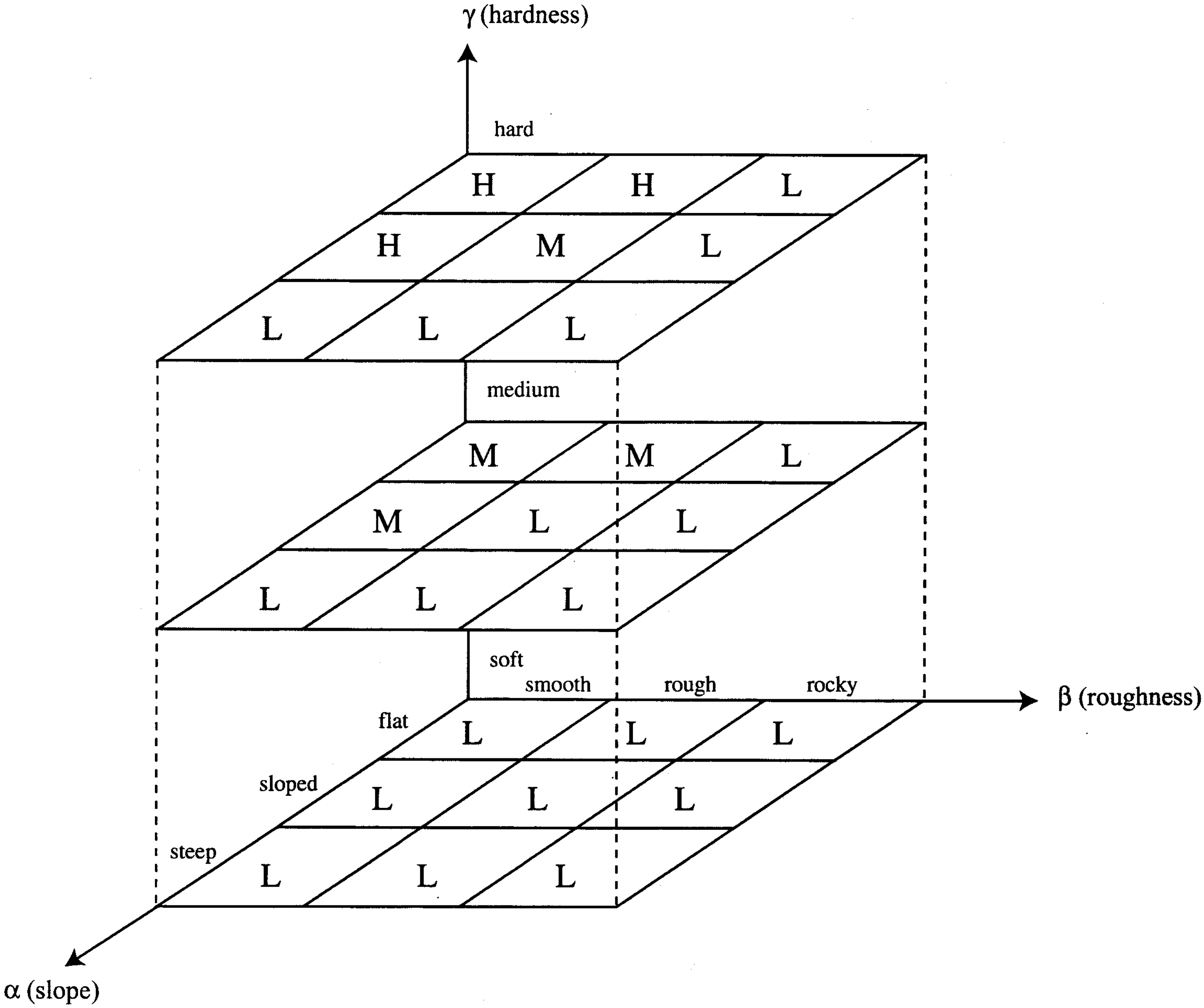

Table 1b. Three-layer rule cube for Traversability Index τ (L=Low, M=Medium, H=High)

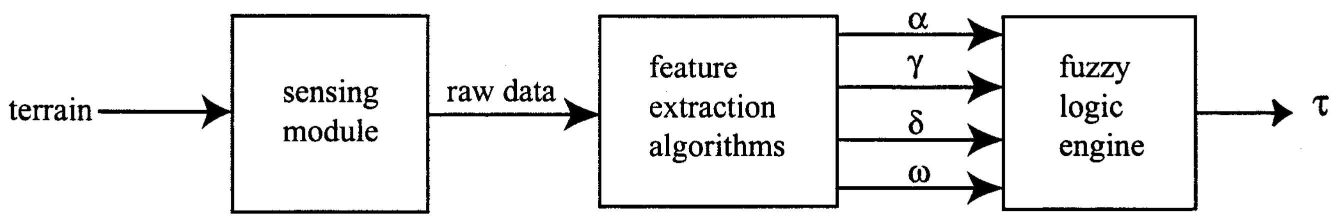

Figure 2a. Sensing and perception stages for terrain traversability evaluation

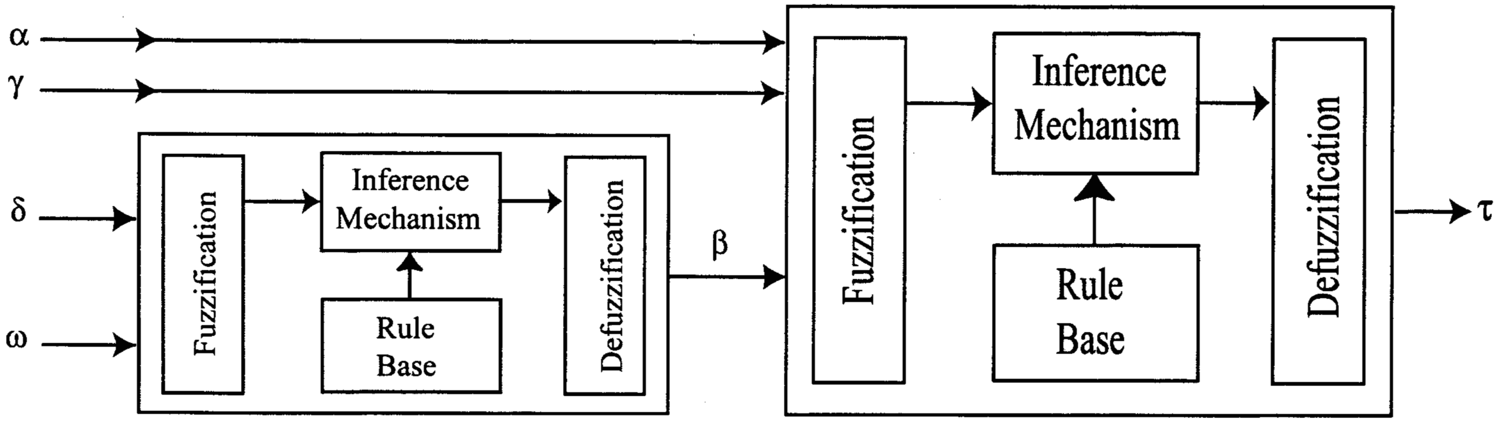

Figure 2b. Block diagram for computation of Traversability Index τ

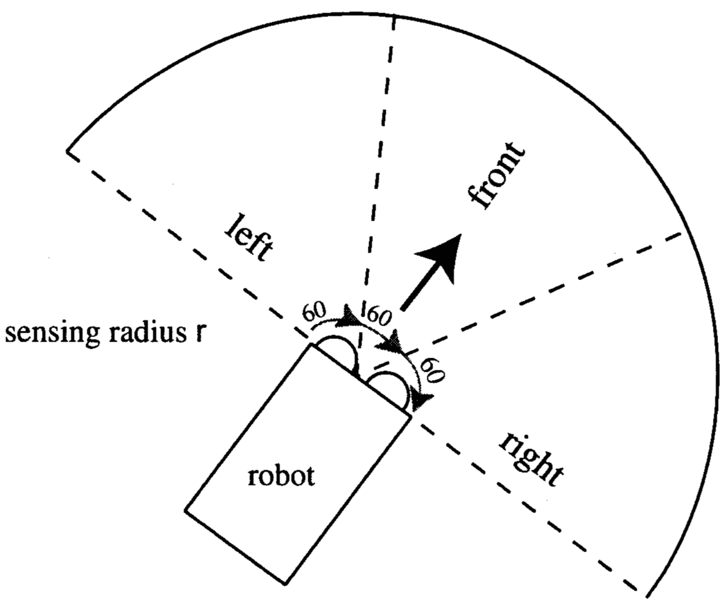

Figure 3a. Definition of traversable regions

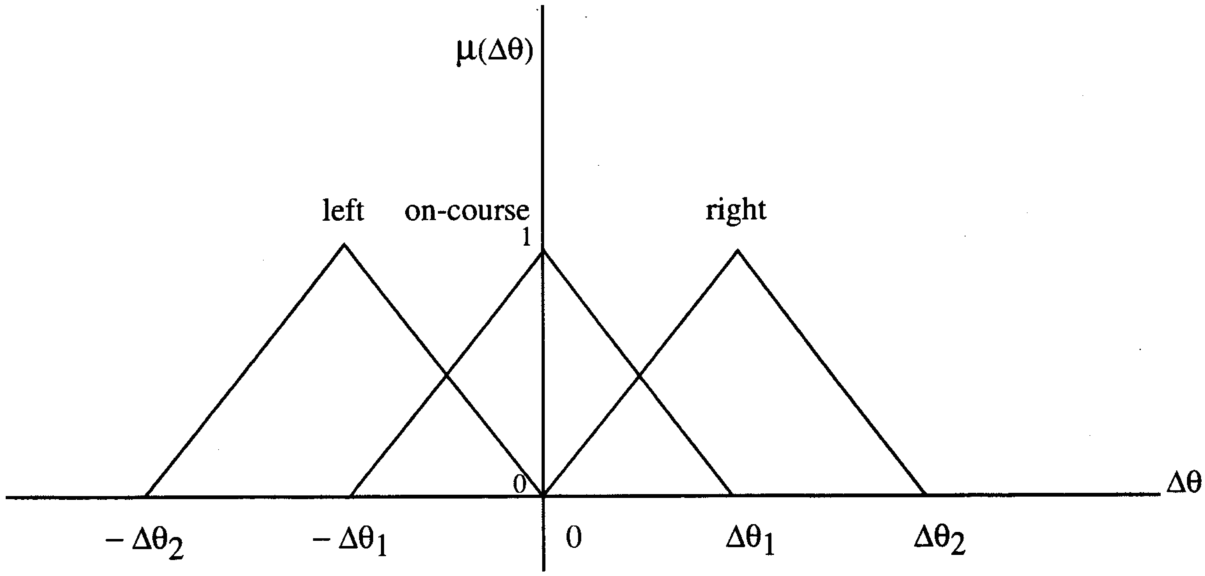

Figure 3b. Membership functions for heading angle change Δθ

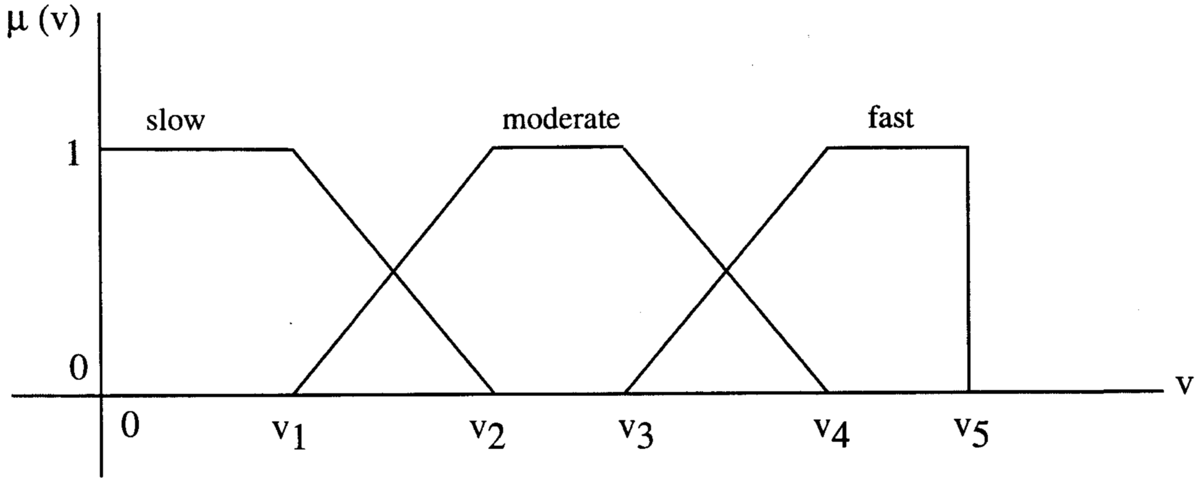

Figure 3c. Membership functions for speed v

τ_ℓ \ τ_r	high	medium	low
high	L	L	L
medium	R	L	L
low	R	R	0

Table 2a. Turn rule set when τ_f is LOW (L=Left turn, R=Right turn, 0= No turn)

τ_ℓ \ τ_r	high	medium	low
high	L	L	L
medium	R	0	0
low	R	0	0

Table 2b. Turn rule set when τ_f is MEDIUM

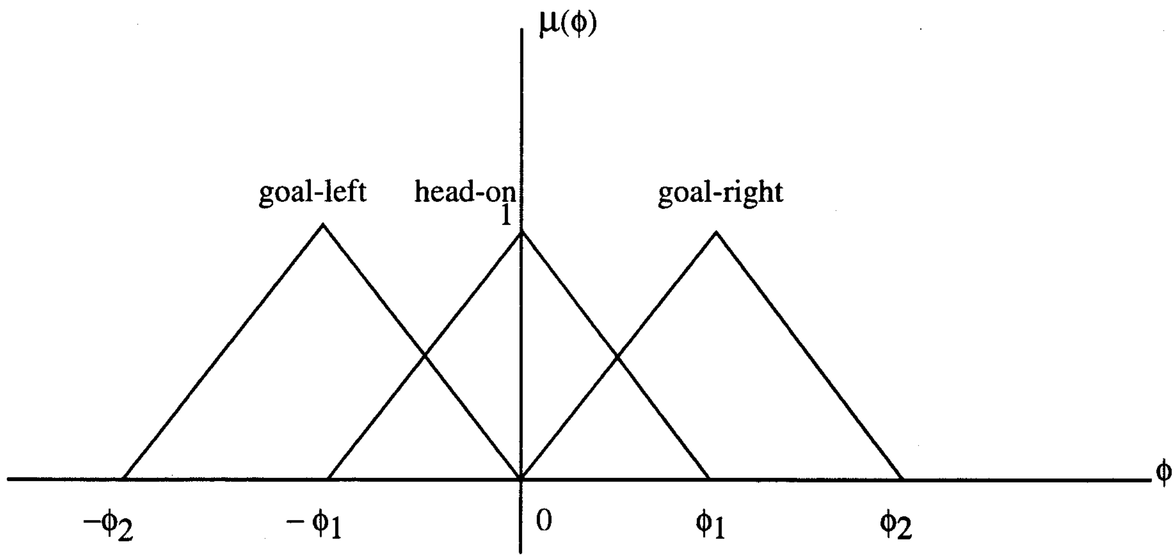

Figure 4a. Membership functions for heading error ϕ

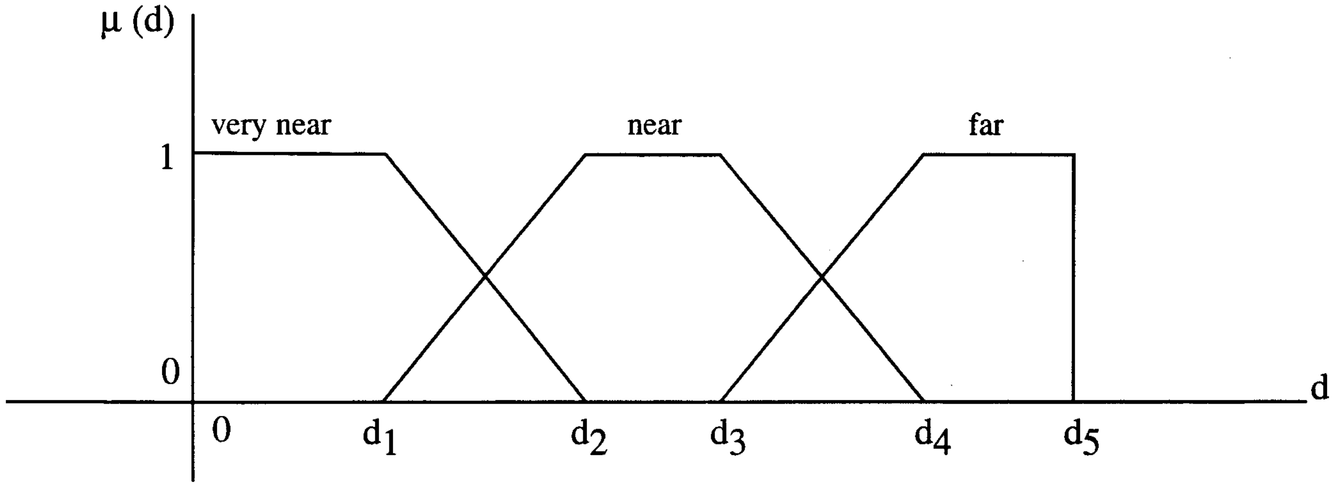

Figure 4b. Membership functions for position error d

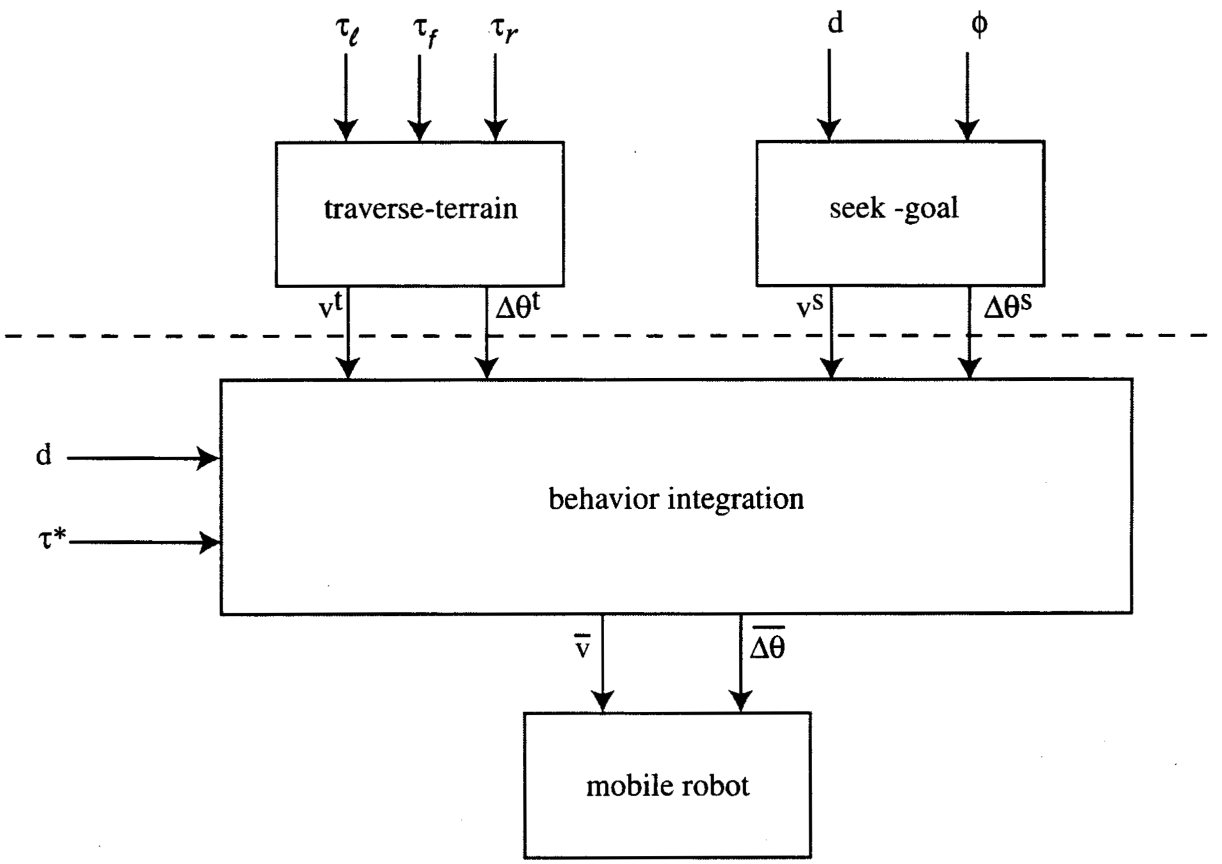

Figure 5a. Two-stage robot navigation procedure

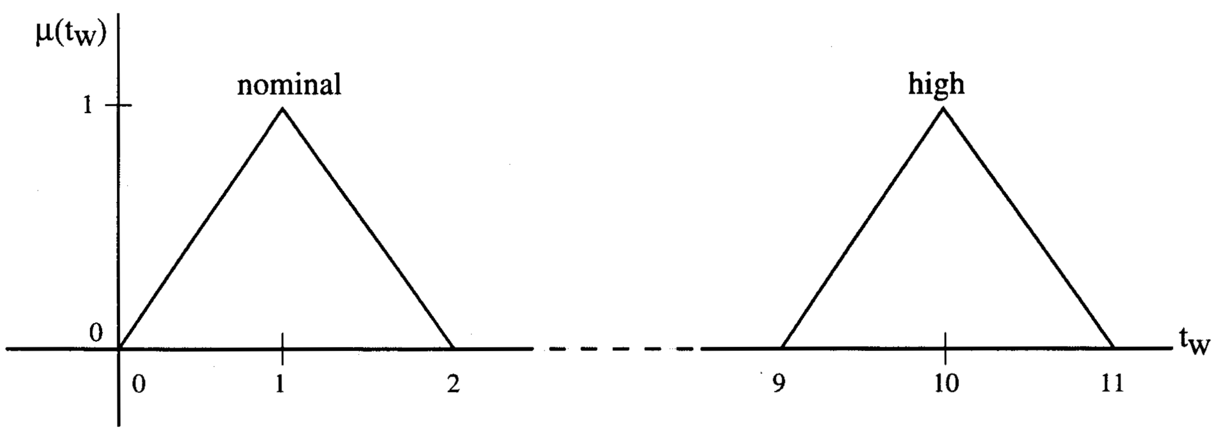

Figure 5b. Membership functions for weighting factor t_w (and s_w)

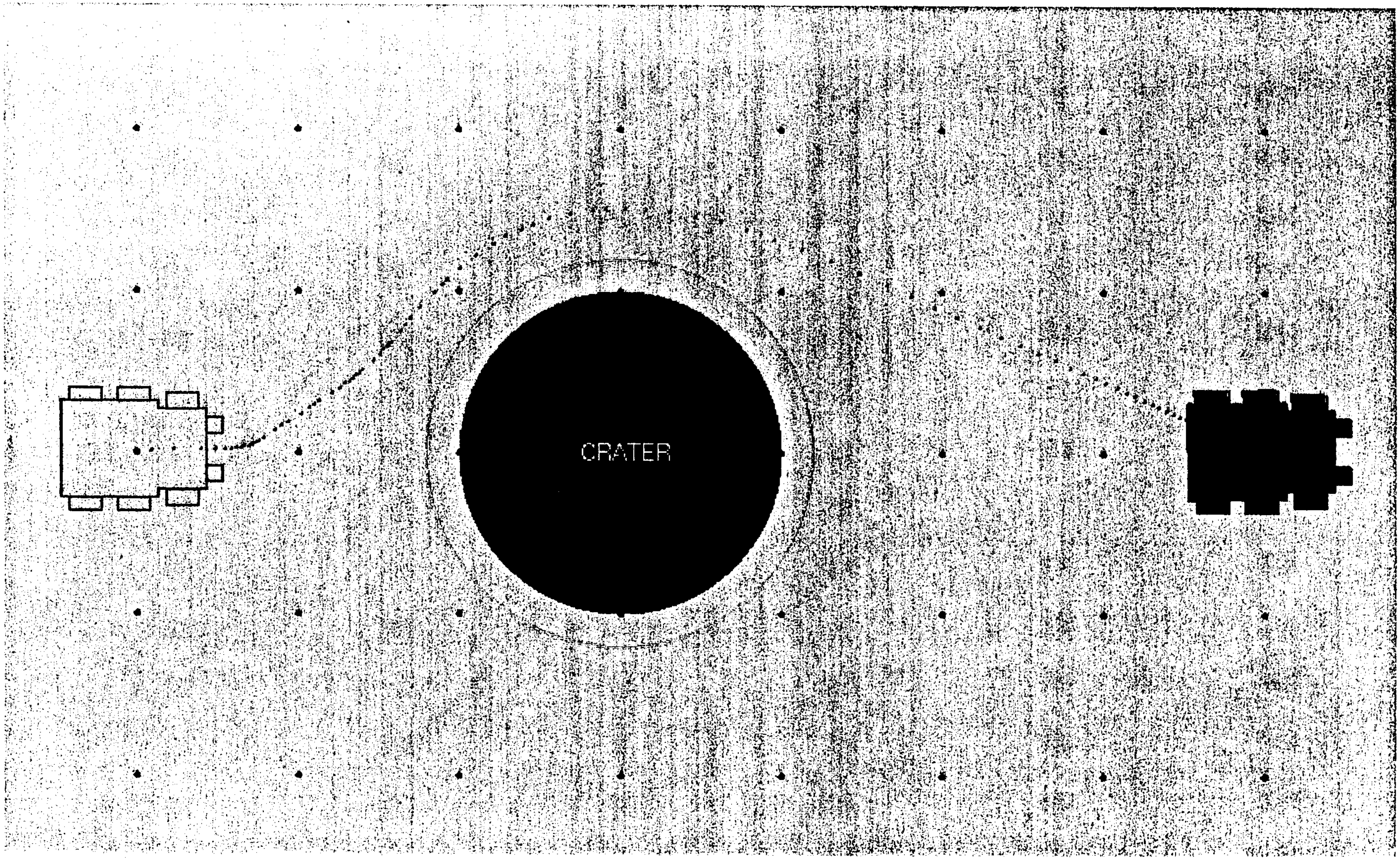

Figure 6a. Simulation of the fuzzy navigation rules - Case study one

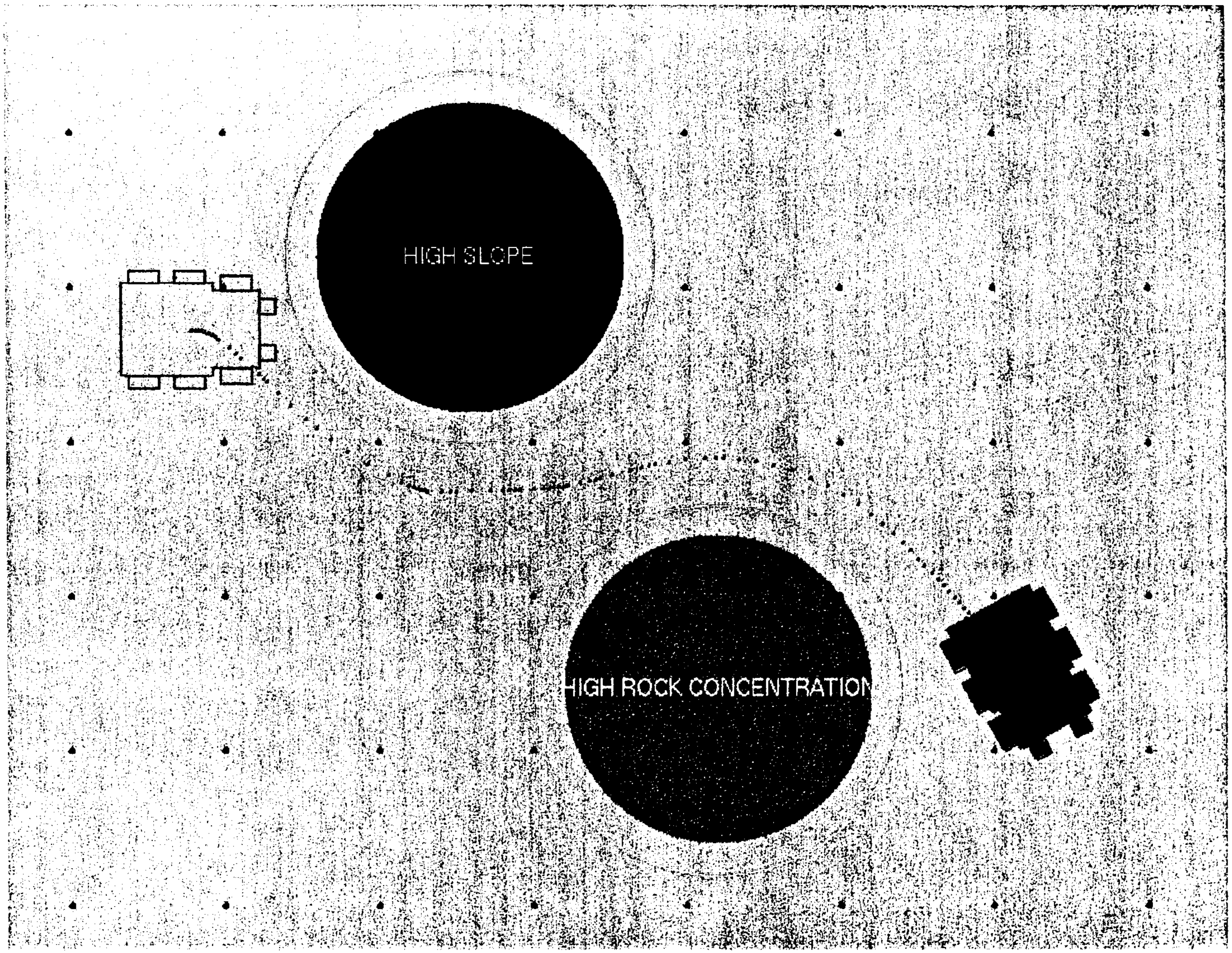

Figure 6b. Simulation of the fuzzy navigation rules - Case study two

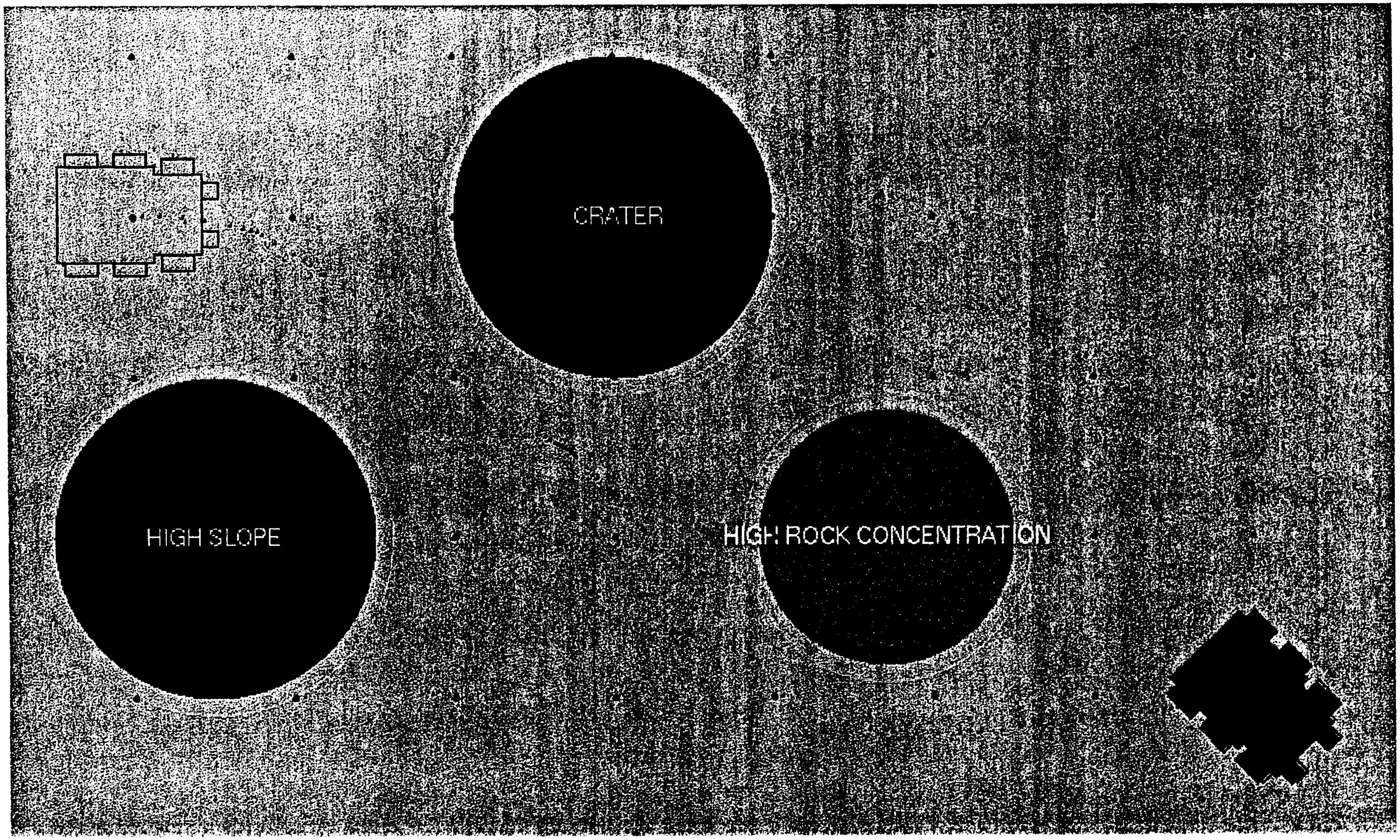

Figure 6c. Simulation of the fuzzy navigation rules - Case study three